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ABSTRACT

Properly manipulated residuals resulting from "status predicting status" regressions constitute a precise and unique measurement of status inconsistency without the definitional and methodological problems and limitations of simple and simultaneous cross-classification techniques associated with the typical "dummy variable regression" approach. Residuals entered as independent variables in multiple regression models including usual status variables allow determination of "inconsistency effects" separate from main effects of status dimensions without sacrificing variability and predictability and precluding analyses of higher-order interaction terms. Several theoretically-based, nonlinear, and modified dummy-variable transformations of residuals are suggested which avoid linear determinancy while measuring the relative influence of status and degrees of directional and nondirectional status inconsistency. Several residual regression models are discussed and empirically compared: 2-variable and multivariable status-inconsistent types and full regression models of statuses and residual inconsistents. Results of tests with selected models predicting political attitude empirically demonstrated the practical and theoretical utility of the residual regression method of measuring status inconsistency effects relative to those of status. Implications for future mobility and status inconsistency research are outlined. (Author)

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AN EMPIRICAL CASE FOR

RESIDUAL MEASURES OF STATUS INCONSISTENCY EFFECTS

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THE PROBLEM

Status inconsistency research has been plagued by the serious methodological dilemma of being unable to differentiate between the main effects of the statuses and any independent effects of the inconsistency due to the inherent identification problem. (Blalock, 1966, 1967; Berry and Martin, 1972) Attempts to overcome these difficulties have led to analyses employing a dummy-variable regression approach which infers the effects of status inconsistency, separate from those of status, by differentiating between additive and interaction models (e.g., Jackson and Burke, 1965; Hodge and Treiman, 1966; Jackman, 1972; Olsen and Tully, 1972; Jackson and Curtis, 1972). Results appear to suggest the theory is more disconfirmed than supported (e.g., Olsen and Tully, 1972; Jackson and Curtis, 1972) but unfortunately tend to be based upon some internally problematic methods of analyzing status inconsistency effects.

In particular, empirical examples of this methodology depend upon the crude technique of cross-classification in which independent (and often dependent) variables are di- and/or trichotomized. In addition to generating gross and somewhat arbitrary distinctions (e.g., using one or more off-diagonal cells to define mobility or status inconsistency), this procedure often results in a loss of variability, which reduces predictability in subsequent analyses. Further losses occur when one or more categories of each independent variable or interaction term must be omitted from the regression analysis of mobility or inconsistency in order to avoid linear determinancy (e.g., Jackman, 1972; Olsen and Tully, 1972). This problem, for example, prevented Jackson and Burke (1965) from testing their regression models using pairs of status dimensions. Also, as Jackson and Curtis (1972) and others point out, employing the method of simultaneous cross-classification produces too few cases in some cells, thereby limiting their analysis to only two status dimensions at a time. Practically speaking, then, their method precludes analyses of higher-ordered interaction terms.[1]

THE RESIDUAL MODELS

A recently proposed set of procedures measures status inconsistency as the residual from a regression model of status congruence. (Lutz and Brod, 1973; Brod and Lutz, 1974) We find that with proper manipulation, this technique avoids the above difficulties and constitute a superior method of measuring the independent effects of status and status inconsistency.[2]

Consider the following general linear, first order regression model:

$$Y + a + bX + e$$

For any data set (meeting the assumptions of regression) the least squares solution will predict the value of the dependent variable from a specified value of the independent variable. The extent to which this prediction is accurate (i.e., $Y_i = Y_i$) can be used as a measure of commonality or "consistency" between the X and Y variables. In most cases, however, the consistency will not be perfect; this lack of consistency is described by the value of the error term (i.e., $e_i = Y_i - \hat{Y}_i$). Thus, the error

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[1]A recent, notable exception to the above is Taylor (1973) who outlines a dummy variable regression strategy appropriate for analyzing general models of balance and dissonance as interaction.

[2]The following section (pp.2-6) constitutes ground already covered in previous papers (cited above) and is included here for those not familiar with this measurement problem and/or our techniques for resolving it. Those already familiar with our work may want to start reading on page 6.

term or residual constitutes a measure of the lack of consistency or "inconsistency" that exists.

In the case of social stratification, status inconsistency is measured by the set of regression residuals resulting from a prediction of one status dimension from another. With proper transformation, the set of residuals is subsequently introduced as an explanatory variable in a second regression model in which the dependent variable is some hypothesized effect due to either status inconsistency or the combined consequences of status inconsistency and individual statuses.

The described residual is a superior measure of status inconsistency in the following respects. (1) Compared to traditional cross-break techniques, the residual gains statistical power by capitalizing on the fact that many statuses such as age, income and years of education are interval measures and also that, in regression analysis, the construction of dummy variables will isolate the effect of each category in nominal or ordinal measures without sacrificing the complete range of variation in the interval measures.

(2) Status inconsistency, defined as a lack of fit between statuses in the form of a regression residual, contains all available information about the extent to which the fitted model fails to explain the observed variation in the dependent status. By visually examining graphic plots of the residuals one can ordinarily determine the extent to which the lack of fit is due to true error (status inconsistency) or to measurement error. Recall that if the residuals are devoid of measurement bias they will meet the assumptions of independence, a zero mean, a constant variance (σ^2), and a normal distribution. The simplest test of these assumptions is accomplished by reviewing such graphic plots of the

residuals as: overall, in time sequence, residual against predicted Y, and residual against independent(s). Visual inspection will ordinarily allow one to determine if a systematic bias is operating; if it is, various corrective steps are available (see Draper and Smith, 1966).

(3) Characteristic of most methods not employing cross classifications is the calculation of the simple difference in status ranks of an individual as a measure of status inconsistency. Such a technique disregards any normative correspondence in status ranks. (Malewski, 1963; Nelson, 1973) The residual measurement technique defines status inconsistency in reference to the mean Y status score at each value of the X status. Hence, to a statistical extent the expected consistency in status ranks is being considered with this method.

(4) Unlike the cross-classification techniques used in conjunction with the dummy-variable regression approach outlined above, the residual regression method accommodates simultaneous analyses of a large number of status dimensions and the larger number of generated interaction terms with a relatively small sample. (5) In addition, analyses can include all categories of all varialbes, both interaction terms and the statuses from which they were generated.

These advantages alone do not solve the identification problem, however. Blalock (1969; 70-71) outlines two alternative solutions. (1) One can introduce new exogenous (and uncorrelated) variables into the equation system to achieve at least an identified, if not over-identified, system. (2) Since the identification problem occurs because the status inconsistency term is a linear function of the status(es) from which it is derived, one can simply incorporate some non-linear transformation of the status inconsistency term in the model. As

Blalock points out such a procedure in fact has greater validity in reference to the original inconsistency theory of Lenski (1954).

In addition, the use of non-linear transformations resolves a difficulty specific to our residual method of deriving status inconsistency measures. Status consistency-inconsistency is a single dimensional concept with inconsistency at one pole and consistency at the other. However, residuals calculated in the manner described above range from large negative to large positive values, with inconsistency at the extremes and consistency toward the center of the continuum. Any one of the following transformations removes this difficulty and simultaneously resolves the identification problem; thus, it is in this sense that our use of residual analysis contributes primarily to the methodological issues of status inconsistency research.

(1) Simply use the absolute value of the residual to determine if consistency in general, regardless of sign, fits the predictive model. (2) Use the square of the residual to clear the sign difference and also to conform to the hypothesis that a very small inconsistency produces relatively little effect while a very large inconsistency produces a greater effect than the simple arithmetic differences (i.e., an exponential effect). (3) Use a modified dummy variable technique to distinguish types of inconsistency (negative and positive) adhering to the idea that these types are significantly different in their effects (e.g., Jackson, 1962). Each residual can be divided into two sub-variables such that in the first all inconsistents of one sign are given their actual value and those of the opposite sign are assigned the score "0". The procedure is reversed in the second sub-variable. By squaring each of these values to include the assumption outlined in

(2) immediately above, the effect of inconsistency by type can be determined and empirically separated from those of degree. (The standard dummy variable approach is outlined by Taylor, 1973.)

Finally, although Blalock (1967) has suggested that evidence of statistical interaction can occur for reasons other than inconsistency effects, his main point is that nonadditivity "cannot unambiguously be interpreted as an 'inconsistency effect,' since the main effects cannot be simultaneously controlled." Thus, justification for treating properly manipulated residual interaction terms as measures of status inconsistency derives from the fact that the residual method can and does simultaneously control for main effects.

Before examining some empirically testable general types of models using residual measures of status inconsistency, consider the following basic status model.

MODEL S

We first isolate a set of status dimensions (X_1, X_2, ...X_n) known to predict a particular dependent variable Y (e.g., political orientation). Assuming linearity, an additive regression model with three status dimensions, for example, would have the form

$$Y = a + b_1X_1 + b_2X_2 + b_3X_3 + e \qquad (1)$$

where interaction is assumed to be zero. This model assumes that the dependent variable is a simple additive function of statuses and provides comparative baseline data for later testing the notion that the predictive power of the status dimensions alone is superior to that of status inconsistency alone or in combination with the statuses. To accomplish this, we now must consider several less parsimonious but testable models employing either residuals alone or various combinations of residuals and statuses.

MODEL I:(E^2)

In this model, the Roman numeral I, refers to the <u>first-order</u> residual (interaction) term and (E^2) indicates that the squared residuals alone are entered stepwise in a regression predicting some dependent index. Continuing with the example with three status variables, an additive model has the form

$$Y = a + b_1(E_{12})^2 + b_2(E_{12})^2 + b_3(E_{23})^2 + b_4(E_{21})^2 + b_5(E_{31})^2 + b_6(E_{32})^2 + e \quad (2)$$

where the first-order interaction term (E_{12}), for example, refers to the set of residuals obtained by regressing X_1 on X_2. In general, k status dimensions determine kC^n_r sets of residuals, where n = K-1≥r, and r refers to the rth-order interaction term(s) (e.g., the three status dimensions in equation 2 define 3(2!/1!·1!), or 6, first-order interaction terms). In addition to first-order terms, higher-ordered terms can be generated to test their predictive power relative to that of other models. For example, Model II:(E^2) would enter squared, second-order residual (interaction) terms alone in a stepwise regression predicting some dependent index. Again using our example of three status dimensions, an additive equasion takes on the form

$$Y = a + b_1(E_{123})^2 + b_2(E_{213})^2 + b_3(E_{312})^2 + e \quad (3)$$

where the second-order term (E_{123}) corresponds to the set of residuals obtained by regressing X_1 on both X_2 and X_3. Thus, three status variables generate two models, Model I:(E^2) and Model II:(E^2), which compare the relative predictive power of first-order square residuals with that of second-order terms. The six status variables (from our empirical example), however, would generate five basic models, i.e., Models I:(E^2)-II:(E^2), incorporating first-order through fifth-order squared residual terms, respectively.

MODEL I: (E^2+S)

The most parsimonious model containing both (S) statuses and squared residuals is generated by simply including first-order interaction terms (as in this example) or higher-ordered sets of residuals in equation (1). Continuing the example with three status variables, an additive model has the form

$$Y = a + b_1X_1 + b_2X_2 + b_3X_3 + b_4(E_{12})^2 + b_5(E_{13})^2 + b_6(E_{23})^2 + b_7(E_{21})^2 + b_8(E_{31})^2 + b_9(E_{32})^2 + e \tag{4}$$

where the first-order interaction term (E_{12}), for example, corresponds to the set of residuals obtained by regressing X_1 on X_2. Properly transformed by the squaring method outlined above, the residuals are entered as independents in a stepwise solution of equation (4) to test for status inconsistency effects controlling for the main effects of the status variables and to assess the explanatory power of inconsistency separate from and relative to that of the statuses from which they were generated.

MODEL I: (E^2+S+k)

Finally, testing for the existence of "supressor variables", the (k) status dimensions, i.e., those <u>not</u> entering (the stepwise regression) equation 1 (Model S), can be reentered stepwise (to determine if some would be significant) in a regression equation predicting the dependent index, holding constant the effects of both status inconsistency and the other (S) statuses.

THE EMPIRICAL TESTS

While many other models are conceivable, the remainder of the paper begins the task of evaluating the utility of the various types of proposed residual measures of status inconsistency (Models I-V) by comparing their predictive power relative to each other, to statuses alone, and to statuses in combination with various types of residuals. To accomplish this, we use the theoretical assumptions underlying the status and inconsistency models outlined above to (1. construct actual inconsistency variables and (2) then test the independent predictive power of these measures relative to that of the status variables from which they were derived. Thus, one can assume that if an inconsistency variable (residual) accounts for more variation in a dependent variable (i.e., it enters the stepwise regression solution earlier) than does a status variable, there is support for the theory of inconsistency effects.

Since our central purpose here is to begin assessing the utility of a method of constructing status inconsistency measures, our primary sampling concern involves achieving variability in our indicators of status and its effects; a simple quota sample, although non-random will suffice. Following this reasoning, test data were taken from an unpublished survey of political attitudes toward U.S. involvement in the Vietnam war. A few months before the end of the war, an attitudinal survey was administered to 252 adults in a midwestern city, with special efforts directed at obtaining a sample representing a diversity of opinion and background characteristics.

Our dependent variable, constituting an additive index of political attitudes toward the Vietnam war, includes 16 variables selected by factor analyzing the pool of survey items. An analysis of variance measure of internal consistency for this index was .85. From the pool of background items, eleven status dimensions were isolated which were thought to explain the derived dependent variable. Without detailing here the various coding procedures used to transform each of these items, it will suffice to say that the set includes both scales and dummy variables measuring age, race, sex, marital status, religious orientation, political orientation, years of education, occupation, student status, military experience, and quality of housing. The intercorrelations among the independent and dependent variables in Table I indicate that of the eleven status variables, seven (63.6%) are significantly related to the dependent Political Attitudes Index.

MODEL S

Following the procedures outlined in Model S provided baseline data regarding the amount of variation in the dependent variable explained by the status variables alone (i.e., assuming no interaction effects due to status inconsistency). Inspection of equation S in Table II shows that of the eleven original status variables, six (54.5%) entered the stepwise regression solution with significant coefficients. In the order of their entry in equation S, attitudes supporting U.S. intervention in the Vietnam war appear to be explained by age, political orientation, education, non-student status, religious orientation, and quality of housing. Squaring the obtained multiple R (.633) indicates that these six statuses alone explain 40% of the variation in the Political Attitudes Index. (Signs and magnitudes of coefficients are located in Equation I, Table III.)

MODEL I:(E^2) and MODEL I:(E^2+S)

These six statuses were then used to derive first-order interaction (residual) terms to measure the degree of various kinds of status inconsistency in accordance with the procedures outlined in Model I:(E^2). Squaring the obtained sets of residuals solved the identification problem and provided status inconsistency measures to test the hypothesis that large inconsistencies produce relatively greater effects than do small ones. In addition, both sets of measures, the residuals and the six statuses from which they were derived, were entered as independents in a stepwise regression equation predicting the Political Attitudes Index (as outlined in Model I:(E^2+S).

TABLE I: Zero-Order Intercorrelations Among Indices of Status and Political Attitude Index

		2	3	4	5	6	7	8	9	10	11	12
1.	Age	-.01	.10	.60**	.13	.40**	-.15*	-.40**	.63**	.14*	.08	.51**
2.	Race		-.02	-.01	.10	-.02	-.04	.03	-.10	-.04	.09	.04
3.	Sex			.17**	-.08	-.17**	.15*	-.04	-.16*	.36**	.05	-.04
4.	Marital Status				.14*	.22*	-.10	-.30**	.55**	.26**	-.13*	.37**
5.	Religious Orientation					.19**	-.08	-.08	.11	.10	.02	.23**
6.	Political Orientation						-.13*	-.15*	.40**	-.06	-.02	.43**
7.	Years of Education							.34**	-.19**	.01	.21**	-.28**
8.	Occupational Status								-.46**	-.18**	.16*	-.24**
9.	Student Status									.07	-.09	.43**
10.	Military Experience										-.06	.20
11.	Quality of Housing											.07
12.	Political Attitudes Index											

* $= p < .05$

** $= p < .01$

TABLE II

Stepwise Multiple Regression Results Showing the Political Attitudes Index as a Function of Statuses Alone (Model S) or in Combination with Various Orders of Residual Measures of Status Inconsistency (Models I-V)

Model Order	Model Type	Squared Multiple R	Multiple R	Standard Error	No. of Index Variables Available	No. of Indep. Variables Entering	Names of Variables and Their Order of Entry*
V	E^2	.1652	.4065	10.1773	6	3	Age = f(all); Rel = f(all); St = f(all)
	E^2+S	.4184	.6468	8.5826	12	8	Age;Pol;Ed; Rel = f(all); St;H; Age = f(all); Ed = f(all)
	E^2+S+k	.4284	.6545	8.5436	17	10	Same as above & Military; Occup.
IV	E^2	.1914	.4375	10.0369	30	4	Age = f(Rel,Pol,St,H); Rel = f(Age,Ed, St,H); St = f(Age, Rel,Ed,H); H = f(Age, Rel,Pol,Ed)
	E^2+S	.4281	.6543	8.5101	36	8	Age;Pol:Ed; Rel = f(Age,Pol,Ed,St); St; Age = f(Rel,Pol,Ed,St); H; Ed = f(Age, Rel,Pol,St)
	E2+S+k	.4381	.6619	8.4706	41	10	Same at above & Military; Occup.
III	E^2	.2568	.5068	9.6932	60	6	Age = f(Rel,Pol,H); Rel = f(Ed,St,H); St = f(Rel,Ed,H); Ed = f(Age,Pol,St); Pol = f(Age,Rel,H); H = f(Age,Rel,Pol)
	E^2+S	.4545	.6742	8.3454	66	10	Age;Pol;Ed; Age = f(Rel,Ed,H); Rel = r(Ed, St,H); H; Pol = f(Rel,Ed,H); St; St = f(Ag Rel,Ed); Pol = f(Rel,Ed,St)
	E^2+S+k	.4679	.6840	8.2780	71	12	Same as first three lines above & Occup; Military; Pol = f(Age,Rel,Ed)
II	E^2	.2705	.5201	9.5722	60	6	Age = f(Rel,Pol); Rel = f(St,H); St = f(Re Ed); Ed = f(Pol,St); H = f(Age,Pol); Pol = f(Age,H)
	E^2+S	.4696	.6853	8.2467	66	11	Age;Pol; Age = f(Rel,Ed); Rel = f(St,H); E Pol = f(Rel,H); H; St = f(Rel,Ed); St; St = f(Pol,H); St = f(Age,Pol)
	E^2+S+k	.4829	.6949	8.1770	71	13	Same as first two lines above & Occup; St = f(Pol,H); St = f(Age,Pol); Military
I	E^2	.3146	.5609	9.2785	30	6	Age = f(Pol); St = f(Rel); Rel = f(Ed); Ed = f(St); St = f(Age)
	E2+S	.4653	.6821	8.2457	36	9	Age;Pol; Age = f(Ed); Rel = f(St); Educ; St = f(Rel); H; Pol = f(H); Pol = f(St)
	E2+S+k	.4653	.6821	8.2457	41	9	Same as above
Model S		.4007	.6330	8.676	11	6	Age,Pol,Ed,St,Rel,H

Age; Pol = Political Orientation; Ed = Education; St = Student Status; Rel = Religion; H = Housing Quality

MODEL I: (E^2+S+k)

Finally, the additional five statuses (according to Model I: (E^2+S+k) were also entered stepwise with the residuals and the six statuses to predict the dependent index. That is, the following stepwise regressions were run predicting the Political Attitudes Index from: (a) squared residuals alone, (b) both the squared residuals and the six statuses from which they were derived, and (c) the squared residuals, the six statuses, and the five statuses remaining from the original eleven. This procedure was adhered to across Models I-V (i.e., models using first-order through fifth-order residual terms and produced the additional 15 regression results in Table II.

ANALYSIS AND RESULTS

The results indicate that Model (E^2), containing inconsistency terms alone, is the poorest predictor across all levels (I-V). That is, status inconsistency measures alone do not perform as well as status variables alone (Model S) or statuses in combination with residuals, Models (E^2+S) and (E^2+S+k). Also, Model S (statuses alone) is a poorer predictor than all models (I-V) containing both statuses and residual measures of status inconsistency, i.e., Models (E^2+S) and $E^2+S+k)$. In addition, there is some support of the idea of "supressor variables," as Model (E^2+S+k) predicted as well (at level I) or better (in levels II-V) than did Model (E^2+S).

A note of caution must be made here, however, since strictly speaking, without proper statistical controls (which are later applied in an example), comparisons should be made only between models with an equivalent number of independent variables available to enter the stepwise regression, e.g., Model S with Model V: (E^2), Model I with Model IV, and Model II with Model III. In the first comparison, Model S (statuses alone) predicts much better than Model V, with fifth-order inconsistency terms alone. Also, in each of the other two comparisons, as well as in the general overall pattern, results indicate that lower-order residuals predict better than those of higher-order, i.e., the simpler, the better.

Based on this finding, Model I:(E^2+S), the most parsimonious model containing both statuses and inconsistency terms, was compared with Model S (statuses alone) to illustrate the general problem of the stability of regression coefficients and to test the comparative predictive power of a more parsimonious model relative to that of a less parsimonious model, i.e., the predictive power of statuses alone relative to that of statuses in combination with first-order residual measures of status inconsistency.

Before proceeding with the example, it should be emphasized that Model I:(E^2+6) was chosen for comparison with Model S, not because it was the best predictor (three others, Models III:(E^2+S+k), II:(E^2+S), and II:(E^2+S+k), predicted better), but because it performed more efficiently, i.e., predicted well with greater parsimony. This choice was not merely aesthetical but practical, since the slightly greater variance accounted for by the less parsimonious models (from levels II and III) is quite likely due to chance alone, i.e., the greater probability of obtaining inflated squared multiple R's due to the much larger pools of independent variables available to enter those stepwise regressions. Attention can now be given to Table III, showing the regression solutions for Model S (statuses only) and Model I:(E^2+S), the most parsimonious model containing both statuses and first-order status inconsistency terms.

Equation I of Table III shows Model S which provided baseline data regarding the amount of variation in the dependent variable explained by the status variables alone (i.e., assuming no interaction effects due to status inconsistency). Squaring the multiple R (.633) indicates that the six statuses alone account for 40% of the variation in the Political Attitudes Index.

Examination of equation II in Table III (a partial solution showing only the first six variables entering the stepwise solution) indicates support for the status inconsistency measures, as they constitue three (or half) of the first six entering variables. In the order of their entry, attitudes supporting U.S. intervention are explained by age, political orientation, age inconsistent with education (i.e., the residual obtained by regressing age on education), religious orientation inconsistent with non-student status, education, and non-student status inconsistent with religious orientation. In addition, squaring the obtained multiple R (.656) indicates that these six variables (three statuses and three inconsistency measures) account for 43% of the variation in the Political Attitudes Scale and, thus, represents a three percent increase over that obtained in equation I (Model S) with the six status dimensions alone.

By continuing the stepwise process, additional support for the status inconsistency measures is gained as they comprise two of the three additional variables entering the final regression solution, equation III of Table II. In the order of their entry, attitudes supporting U.S. intervention in Vietnam are additionally explained by quality of housing, political orientation inconsistent with quality of housing, and political orientation inconsistent with non-student status.

TABLE III

Stepwise Multiple Regression Solutions of Equation I (Model S), Equation II (Model I, partial solution), and Equation III (Model I, full solution) Showing the Political Attitudes Index as a Function of Status Dimensions Alone or in Combination with First-order Residual Measures of Status Inconsistency

				Status Dimensions						Residual Measures of Status Inconsistency					
				Age	Religious Orientation	Political Orientation	Education	Non-student Status	Quality of Housing	Non-student Status Inconsistent with Religion	Age Inconsistent with Education	Religious Orientation Inconsistent with Non-student Status	Political Orientation Inconsistent with Non-student Status	Political Orientation Inconsistent with Housing	Constant
				Unstandardized Regression Coefficients											
Equation	R	R^2	Standard Error	X_1	X_2	X_3	X_4	X_5	X_6	Z_1	Z_2	Z_3	Z_4	Z_5	C
I.	.633	.401	8.66	.24 (.07)*	1.26 (.53)	1.50 (.41)	-3.24 (.89)	4.60 (1.46)	.71 (.34)						32.56
II.	.656	.430	8.46	.52 (.08)		1.72 (.39)	-2.45 (.86)			-26.55 (9.99)	-.02 (.00)	-.79 (.23)			40.33
III.	.682	.465	8.25	.52 (.08)		1.80 (.39)	-2.95 (.86)		.92 (.33)	-31.85 (9.90)	-.02 (.00)	-.67 (.23)	.47** (.35)	-1.06 (.37)	39.80

*Numbers in parentheses represent the standard error of the estimate.
**Except for this result ($p < .10$) all coefficients are significant beyond the .005 level.

Squaring the multiple R (.682) obtained in the final regression indicates that (1) these variables account for an additional 3.5% of the variation of Y over that obtained in equation II and (2) the status inconsistency measures together with the status variables from which they were derived account for 6.5% more variation in the Political Attitudes Index than do the status dimensions alone.

As noted before, some caution is necessary when generalizing from results of analyses using R^2, particularly if generated by a stepwise solution. That is, the larger the pool of independent variables from which to select, the greater the likelihood of a certain amount of upward biasing of R^2 due to chance. This means that in subsequent samples, some amount of shrinkage in R^2 can be expected. Increasing sample size should help offset but not entirely eliminate the problem of bias; therefore, some estimate of the degree of shrinkage should be made. Basically there are two approaches to the validation of regression analysis results (see Kerlinger and Pedhazur, 1973).

(1) Optimally, stepwise regression analysis requires double cross-validation. Thus, the sample was randomly split in half and stratified on the basis of occupational categories. For each of the two models, i.e., for Model S and for Model I: (E^2+S), two new sets of regression coefficients were generated, one set from group 1 data and another set from group 2 data. Group 2 Political Index scores were then correlated with those predicted using coefficients obtained with group 1 data; the multiple R achieved for Model S was .568 and that obtained for Model I was .486. When the procedure was reversed (i.e., group 1 scores were correlated with those obtained using group 2 coefficients), multiple R was .654 for Model S and .559 for Model I. As expected, Model S, the

more parsimonious of the two, achieved slightly higher miltiple R's; however, both models exhibited a fairly high degree of stability in comparison to the original multiple R's (.633 for Model S and .682 for Model I).

(2) Also, when all the independent variables are included in the regression, shrinkage in R^2 can be estimated by the following formula: $\hat{R}^2 = 1 - \frac{N-1}{N-m-1} K^2$, where $\hat{R}^2$ = the estimated squared multiple correlation in the population; $K^2 = 1 - R^2$; N = size of the sample; m = number of independent variables. When Model S is extended to include all eleven original status variables, R^2_S (the obtained squared multiple correlation) equals. 412, and $\hat{R}^2_S$ (the shrunken squared multiple correlation) equals .385, a loss of 2.7%. When Model I is extended to include all 6 statuses and all 30 status inconsistency measures, $R^2_I = .509$ and $\hat{R}^2_I =$ .426, a difference of 8.3%. Of importance here is the fact that after shrinkage in both models is accounted for, the estimated squared multiple correlation achieved by Model I is still 4.1% greater than that obtained with Model S (i.e. $\hat{R}^2_I - \hat{R}^2_S = 4.1\%$).

Finally, problems of parsimony and stability may be resolved in part by the nature of status inconsistency itself. For example, we find that status inconsistency measures of a similar kind tend to be extremely interrelated, as illustrated in five of the six categories in Table IV (all except student status). Utilizing these highly intercorrelated residual measures to create indices of various kinds of status inconsistency should tend to produce even greater stability and parsimony in these status inconsistency models.

The results of this initial testing of Model I:$(E^2$+S) (the most parsimonious model involving both statuses and first-order status incon-

TABLE IV

Zero-Order Intercorrelations Among Squared Residual Measures of the Six Kinds of Status Inconsistency

Religion as a function of:	Age	Pol.	Ed.	St.	H.
Age	1.000				
Pol.	.986	1.000			
Ed.	.994	.985	1.000		
St.	.997	.987	.993	1.000	
H.	.997	.985	.997	.996	1.000

Political as a function of:	Age	Rel.	Ed.	St.	H.
Age	1.000				
Rel.	.534	1.000			
Ed.	.575	.853	1.000		
St.	.711	.525	.596	1.000	
H.	.579	.885	.949	.600	1.000

Education as a function of:	Age	Rel.	Pol.	St.	H.
Age	1.000				
Rel.	.990	1.000			
Pol.	.992	.994	1.000		
St.	.993	.990	.993	1.000	
H.	.968	.983	.979	.976	1.000

Student as a function of:	Age	Rel.	Pol.	Ed.	H.
Age	1.000				
Rel.	-.075	1.000			
Pol.	.110	.199	1.000		
Ed.	-.088	.164	.067	1.000	
H.	-.229	.232	.049	.287	1.000

Housing as a function of:	Age	Rel.	Pol.	Ed.	St.
Age	1.000				
Rel.	.993	1.000			
Pol.	.992	.999	1.000		
Ed.	.930	.934	.938	1.000	
St.	.976	.990	.992	.933	1.000

Age as a function of:	Rel.	Pol.	Ed.	St.	H.
Rel.	1.000				
Pol.	.837	1.000			
Ed.	.960	.812	1.000		
St.	.802	.713	.793	1.000	
H.	.986	.851	.955	.786	1.000

sistency terms) appear in every respect to confirm the utility of measuring status inconsistency as the squared residual from a regression model of status congruence. Further tests of these and other models are currently in progress. For example, transforming the sets of residuals using the modified dummy variable method outlined above, additional sets of models can be derived to test for the effects of directional types of status inconsistency separately, or in conjunction with the squared residuals, to assess the effects of both directional and nondirectional status inconsistency, holding constant the effects of status.

CONCLUSION

The applicability of residual analysis as a general approach to the study of interaction is also obvious, particularly in the case of social mobility. Despite attempts at synthesis, the two theoretically distinct traditions of mobility and inconsistency have remained, in part because no methodology has provided an adequate means of empirically assessing the relative merits of either. The residual regression techniques outlined here provide such a methodology, that is, a method for analyzing the relative influence of social mobility, status, and status inconsistency. One of the authors, for example, is currently using U.S. census data samples to assess the relative effects of status and status inconsistency on occupational mobility.

If the above set of procedures continues to survive the test of empirical inquiry, it seems highly useful for the purposes of theory building to begin development of an inventory of the models most supported in reference to various dependent variables. As Jackson and Curtis (1973) remind us, some dependent variables (especially political liberalism) are repeatedly associated with certain status characteristics while others are not. As the methodology develops, rigorous and systematic efforts will be undertaken to codify these relationships.

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